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Research & Development and Long-Term Economic Growth: A Bayesian Model Averaging Analysis

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Research & Development and Long-Term Economic Growth: A Bayesian Model Averaging Analysis

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Abstract:
We examine the effect of research and development (R&D) on long-term economic growth using the Bayesian model averaging (BMA) to deal rigorously with model uncertainty. Previous empirical studies investigated the effect of dozens of regressors on long-term growth, but they did not examine the effect of R&D due to data unavailability. We extend these studies by proposing to capture the R&D intensity by the number of Nobel prizes in science. Using our indicator, our estimates show that R&D exerts a positive effect on long-term growth with posterior inclusion probability of 0.25 using our preferred parameter and model priors.

Keywords: research and development, economic growth, Bayesian model averaging.

JEL: O30, O32, O10.

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1 Introduction

The positive effect of research and development of long-term economic growth is well established in economics literature and numerous endogenous growth theory models put forward that research and development is a key for growth (Barro and Sala-i-Martin, 1995). However, the empirical evidence is more scant and available either for a single country or a limited group of developed countries (Hasan and Tucci, 2010). The underlying reason is that more comprehensive R&D data has become available for a wider set of countries only recently (for example, R&D expenditures from about mid-1990s) and R&D is likely to influence the economic growth in the long-term. From empirical perspective, this poses challenges to identify the effect of R&D on long-term growth.

The current empirical literature on long-term growth has emphasized the role of model uncertainty (e.g. the uncertainty about "correct" model specification). The number of potential determinants of long-term growth is plentiful and many earlier studies have chosen the set of regressors in growth regression in *ad hoc* way, to a large extent. To deal with model uncertainty formally, Bayesian model averaging (BMA) techniques have recently gained popularity to study the determinants of long-term growth (Fernandez et al. (2001a), Durlauf et al. (2008), Ley and Steel (2009) or Eicher et al. (2011)). BMA has also been recently introduced to political science by Montgomery and Nyhan (2010) and is well established statistical technique also in natural sciences.

In principle, BMA is employed to cross-country growth linear regression. It is noteworthy that BMA offers several advantages. First, the number of regressors is limited only by the number of countries included in the regression analysis and in consequence a large number of regressors can be examined (for example, Fernandez et al. (2001a) and Eicher et al. (2011) examine 41 regressors). In consequence, this decreases omitted variable bias and many competing theories can be put in test jointly. Second, BMA introduces a rigorous way how to average across the models and thus, examine the robustness of results more systematically. Third, BMA gives a so-called posterior inclusion probability, i.e. an estimate of probability that given regressor is included in "correct model".

As noted above, the set of regressors included in regression analysis in previous studies is large. Nevertheless, neither any of previous studies on long-term growth using BMA include the R&D indicators due to data unavailability. To acknowledge the endogeneity in growth regressions in a full manner, previous studies explain the long-term growth (more specifically, typically growth from

1960s to present) using the regressors that are exogenous and therefore mostly based on the data before 1960 (or are exogenous by definition such as Asian dummy or access to coast). In consequence, the data on R&D are omitted, as they are very scarce for the aforementioned period.

This paper proposes to proxy the efforts various countries put in the research and development by the number of Nobel prizes received by the laureates from specific countries. Nobel prizes are the most reputable awards in science and it is very likely that the laureates will be affiliated with institutions in countries that devote more resources on R&D. First, we show the number of Nobel prizes are correlated with the research and development expenditures in the long-term. Second, we include our R&D indicator in the dataset employed first by Fernandez et al. (2001a) and subsequently by a number of other studies (more on this below), and examine its effect on economic growth.

Subject to various sensitivity tests, our results show that the research and development exhibits a positive effect on long-term economic growth. The posterior inclusion probability for our preferred prior structure is 0.25, which is not high, but comparable to variables such as exchange rate distortions, the share of primary exports or wars.

The paper is organized as follows. Section 2 briefly introduces the Bayesian model averaging. Section 3 presents the data. The results are available in section 4. Conclusions are provided in section 5. Appendix with additional results follows.

2 Bayesian Model Averaging

This section gives a brief introduction to the Bayesian model averaging. We heavily follow Eicher et al. (2011). Other excellent treatments of BMA are available in Koop (2003), Koop et al. (2007), Feldkircher and Zeugner (2009), Ley and Steel (2009) or Montgemery and Nyhan (2010) to name few.

Suppose we have a dependent variable Y (long-term GDP growth in our context) with a number of observations n (the number of countries) and k regressors $X_1.....X_k$. The standard procedure would be to estimate one model $Y = \alpha_1 X_1 + .. + \alpha_k X_k + e$, where $e \sim N(0, \sigma^2 I)$ (assume that X_1 is a constant). However, in many applications there is a substantial uncertainty, which of possibly plentiful X's should be included. In principle, there are $l = 2^k$ subsets of X's that can be considered and therefore $M_1....M_l$ models (regressions) to be examined. Let us denote the vector of parameter of i-th model as $\theta_i = (\alpha, \sigma)$ .The likelihood function of i-th model, $pr(D \mid \theta_i, M_i)$ summarizes all the information about θ_i based on available data D. The marginal likelihood, the probability density of the data, D, conditonal on M_i can be written as follows

$$pr(D \mid M_i) = \int pr(D \mid \theta_i, M_i)\, pr(\theta_i \mid M_i)\, d\theta_i, \tag{1}$$

e.g. the marginal likelihod is a product of the likelihood function and prior density $pr(\theta_i \mid M_i)$ integrated over parameter space. Using $pr(D \mid M_i)$ one can derive the prior probability that M_i is a correct model, this is denoted as $pr(M_i)$. Bayes's theorem gives the posterior model probability of M_i, $pr(M_i \mid D)$,

$$pr(M_i \mid D) = \frac{pr(D \mid \theta_i, M_i)\, pr(M_i)}{\sum_{l=1}^{i} pr(D \mid M_l)\, pr(M_l)} \tag{2}$$

the posterior inclusion probability of given regressor, $pr(\alpha_j \neq 0 \mid D)$, is then received by taking a sum of posterior model probabilities across those models that include the regressor. Posterior inclusion probability is of primary importance here, since it indicates what is the probability that given regressor has an effect on dependent variable (long-term economic growth). This approach has been recently generalized to panel data setting to explicitly account for unobserved heterogeneity among countries (Benito, 2011).

It is computantionally prohibitive to evaluate all the posible models - 2^{42} in our case and we use MC^3 to reduce the computational requirements (Madigan and York, 1995). approximates the posterior distribution of model space by simulting a sample from it. We take 1 000 000 burn-ins and 3 000 000 draws, which leads to a sufficiently high correlation between exact and MC^3 posterior model probablities(about 0.99).

2.1 Parameter priors

Parameter priors have to be specified in order to implement BMA. In general, priors specify researcher's information or beliefs before seeing the actual data.

Since the degree of belief is not particularly high in the growth context, uninformative priors are typically employed.The priors affect the marginal likelihood in (1) and there is a discussion in literature, which parameter priors (as well as model priors, more on this below) are preferable (Eicher et al. (2011) and Ley and Steel (2009)). This is examined by evaluating predictive performance of the model. For example, among 12 candidate parameter priors, Eicher et al. (2011) find that the Unit Information Prior (UIP) with uniform model prior tend to provide more accurate predictions than the other considered priors. On the other hand, Feldkircher and Zeugner (2009) prefer hyper g-priors. To deal with the issue, we carry out the estimations using several parameter priors (as well as model priors) to shed light on the robustness of results.

The first prior is defined as follows.

$$pr\left(D \mid M_i\right) \approx c - 1/2BIC_i, \tag{3}$$

where

$$BIC_i = n\log\left(1 - R_i^2\right) + p_i\log\left(n\right) \tag{4}$$

In (3) and (4), c is a constnant, R_i^2 stands the coefficient of determination and p_i for the number of regressors. This prior is typically labelled as UIP.This prior is typically labelled as UIP. This prior depends on data and it has been questioned, whether this commonly used prior is valid for Bayesian analysis. Next, we consider the following prior, so-called g-prior, proposed by Fernandez et al. (2001b):

$$pr(\alpha_1 \mid M_i) \propto 1, \tag{5}$$

$$pr(\sigma \mid M_i) \propto 1, \tag{6}$$

$$pr\left(\alpha^{(k)} \mid \sigma, M_i\right) \sim N\left(0, \left(g_k Z^{(k)\prime} Z^{(k)}\right)^{-1}\right), \tag{7}$$

where $Z^{(k)}$ denote the matrix of size $n \times p_k$ with p_k demeaned regressors included in M_i. It is noteworthy that the values of g close to zero imply less informative prior and $g = 1$ gives the same weight to the information contained in data and in prior. Two different values of g are examined. First, $g = 1/\max\left(N, k^2\right)$ is the one preferred by Fernandez et al. (2001b) called BRIC. Second, $g = 1/\left(\ln N\right)^3$ corresponds to Hannah-Quinn criterion. The third commonly employed g-prior set $g = 1/k^2$ (Foster and George, 1994), but this is in our setting identical to $g = 1/\max\left(N, k^2\right)$.

Next, we also use parameter priors not employed previously in the growth literature (except Feldkircher and Zeugner, 2009), the so-called hyper-g prior (Liang et al, 2008).

$$\pi(g) = \frac{a}{a-2}(1+g)^{a/2}, \tag{8}$$

We use two different hyper-g priors. The first one sets the prior expected value of shrinkage factor to correspond to UIP, the second one sets it to conform to BRIC. All in all, this makes five different parameter priors that we employ for the empirical investigation of long-term economic growth.

2.2 Model priors

Two different model priors - uniform and random binomial - are investigated. We start with uniform model prior, which gives equal prior probability to all models M_i. In consequence, $pr\left(M_i\right) = 1/L$ for each i. Next, more general model prior is employed.

$$pr\left(M_i\right) = \Pi_{j=1}^{p} \pi_j^{\delta_{kj}} \left(1 - \pi_j\right)^{1-\delta_{kj}}, \tag{9}$$

where $\delta_{kj} = 1$, if X_j is included in M_i, and 0 otherwise and π is treated as random variable drawn from $Beta\left(1, \frac{1-\pi}{\pi}\right)$ distribution (Ley and Steel (2009)).

3 Data

We use the data from Fernandez et al. (2001a). The benefit of using this dataset is that it has been analyzed by a number of researchers afterwards (Koop (2003), Koop et al. (2007), Ley and Steel (2009) or Eicher et al. (2011)) and substantial sensitivity analysis is thus available. The original dataset contains 41 regressors from 72 countries leading to a total of 241 models (more than 2 trillion).

The dataset is representative, there are both developed and developing countries and the regressors include various economic, political, geographical, demographic social or cultural variables considered to be important by previous literature. The list of countries and regressors is available in the Appendix. The dependent variable, economic growth, is defined as the change in the growth in 1960-1992.

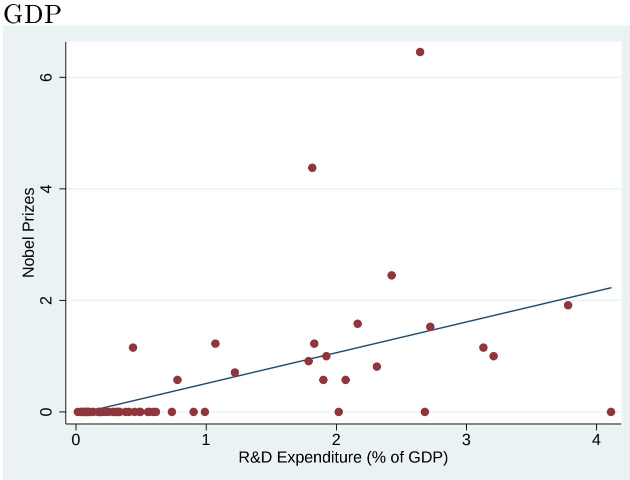
Since ordinary least squares model enters into the BMA, it is important that the regressors are exogenous (e.g. are not correlated with the error term). Some regressors such as geographical variables are clearly exogenous to economic growth, while for others exogeneity is assured by using the data before 1960 or at worst from 1960s-1970s, where applicable. Comprehensive R&D data such as the ratio of expenditures on R&D to GDP is not available for this period and in fact these data are available for a sufficient number of countries only from mid-1990s onwards. Therefore, we propose to proxy the R&D intensity with the number of Nobel prizes in science by countries. We use the prizes in 1945-1975 to have sufficient time coverage as well as heterogeneity. We believe that our indicator of R&D intensity is exogenous to economic growth in 1960-1992, since the prizes are given with a substantial lag typically of more than two decades after the scientific discovery.

Our R&D indicator, RD, is calculated as follows:

$$RD_j = \sum_{i=1}^{4} \sum_{t=1945}^{1975} \left(\frac{1}{n}\right)_{i,t} \tag{10}$$

where i stands for the scientific field in which the laureate received the prize (physics, chemistry, medicine and economics) and t represents the year in which the laureate were honored. n stands for the number of laureates that was given the prize in particular field and given year. For example, if three laureates shared the prize in physics in year t, then $1/n = 1/3$. RD_j for country j is obtained by summing up $1/n$ over all the years and fields. It is noteworthy that the affiliation of laureate in the year the prize was given (and not citizenship or the place of birth) determines to which country the value of $1/n$ is assigned (the source of data is a official website of Nobel Foundation www.nobelprize.org).

Figure 1: R&D Indicator based on Nobel Prizes and the R&D Expenditures to GDP



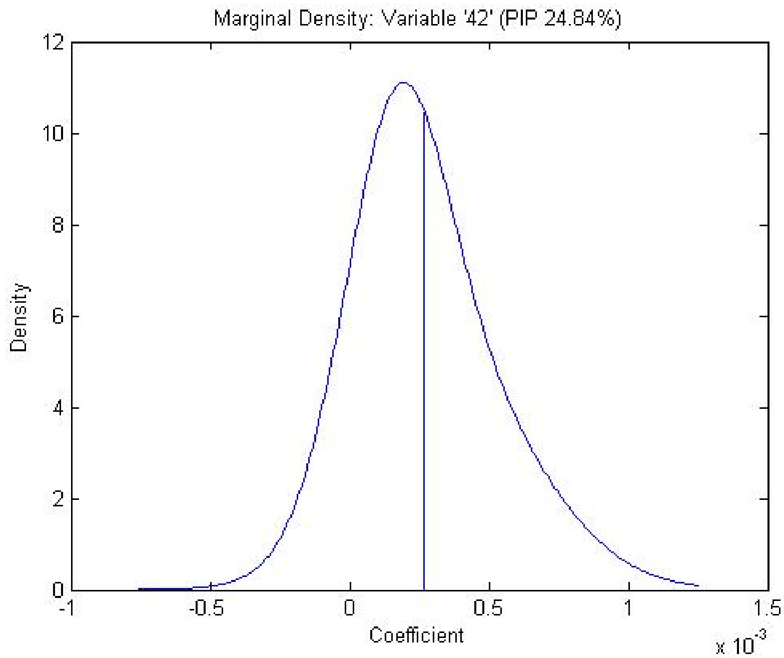
This is so, as we believe that affiliation most closely captures which country invests more in its R&D. Alternatively, we calculated the R&D indicator not adjusting for the fact that prizes are often shared, but the regression results remained largely unchanged and are available upon request.

To motivate the use of our R&D indicator based on Nobel prizes, Figure 1 gives the scatter plot of R&D indicator ($\sqrt{RD_j}$) and the average share of R&D expenditures to GDP in 1996-2007. Visual inspection suggests that the link between these two variables is clearly positive. Two outliers are evidently present (US and UK) and we re-estimate our model without US and UK to shed light on the extent these outliers are eventually driving the results on the estimated effect of R&D on long-term economic growth.

4 Results

This section present the results of BMA analysis of long-term economic growth and discusses the effect of R&D indicator on growth. First, some baseline estimates are provided and substantial sensitivity analysis follows. The results are obtained in a chain of 2 million recorded draws (after 1 million burn-ins) and 1576409 models are visited (e.g. 3.6e-05% of model space)."UIP" hyper g-prior and random binomial model prior is used as baseline and the results are available in Table 1. The baseline choice is motivated by the simulations available

Figure 2: R&D Indicator based on Nobel Prizes and the R&D Expenditures to GDP



in Feldkircher and Zeugner (2009), who show that hyper g-prior is preferable in terms of the risk of mispecification and predictive ability. Table 1 contains the posterior inclusion probability (PIP) as well as the posterior mean and standard deviation for each regressor.

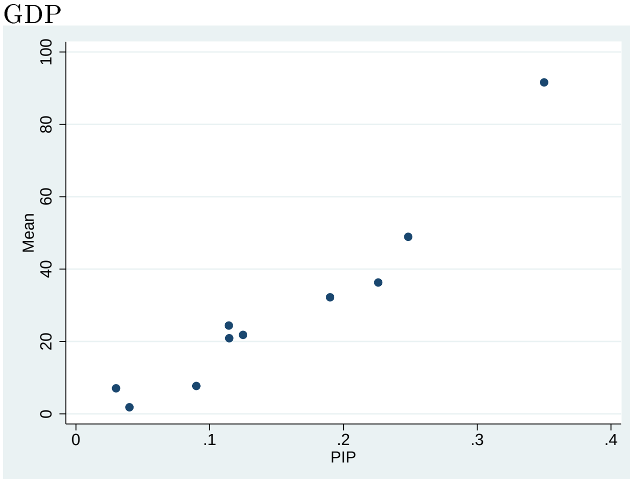
Our results are largely in line with Fernandez et al. (2001a) both in terms of the ranking as well as the value of PIPs (with some exemption such as the variable "no. of years open economy" and Spanish colony dummy). The results suggest that the R&D indicator, although with rather lower posterior inclusion probability of 0.25, exerts a positive effect on long-term growth. We hypothesize that the lower PIP can be related to lower variability of our R&D indicator, as only 19 countries out of 72 received Nobel prizes, but comparing all regressors according to the coefficient of variation suggest that R&D indicator exhibits more variability than many regressors. Figure 2 shows the posterior density of the coefficient on R&D indicator.

Next, we examine the sensitivity of the R&D indicator effect on economic growth on different parameters and models prior structures. Combining all prior

Table 1: Marginal Evidence of Importance

Regressors	PIP	Post Mean	Post SD
GDP level in 1960	1.00	-0.0158818	0.00316847
Fraction Confucian	0.99	0.0597092	0.0157115
Life Expectancy	0.97	0.000843323	0.000304049
Equipment investment	0.91	0.12709	0.0633071
Sub-Saharan dummy	0.88	-0.0153761	0.00826007
Fraction GDP in mining	0.79	0.0302984	0.0207787
Fraction Hindu	0.68	-0.0445141	0.0410678
Non-equipment investment	0.68	0.0336193	0.0296078
Rule of law	0.65	0.00759643	0.00715747
Degree of capitalism	0.62	0.00124075	0.00125917
Size labor force	0.61	1.47E-07	1.54E-07
Fraction Muslim	0.59	0.00699517	0.00787046
Fraction Protestants	0.58	-0.0060257	0.00671034
Black market premium	0.55	-0.00388477	0.00444967
Latin American dummy	0.54	-0.00547318	0.00670768
Higher school enrollment	0.54	-0.0476613	0.0558694
Ethnolinguistic fractionalization	0.53	0.00591381	0.00691384
Primary school enrollment	0.47	0.00794108	0.0109484
Civil liberties	0.42	-0.00088533	0.00148985
Fraction Buddhist	0.41	0.00393154	0.00645809
Spanish colony dummy	0.40	0.0033696	0.00570302
Number of years open economy	0.39	0.003012	0.00605768
Fraction of pop. speaking English	0.37	-0.00260113	0.00450231
French colony dummy	0.37	0.00231528	0.00419116
Outward orientation	0.34	-0.00102988	0.00194215
Political rights	0.34	-0.000390709	0.00107803
Age	0.33	-1.28E-05	2.51E-05
War dummy	0.32	-0.000994977	0.00205677
British colony dummy	0.31	0.00106028	0.00306014
Fraction Catholic	0.30	-0.00039819	0.00381725
Public education share	0.28	0.0386838	0.095647
Primary exports	0.26	-0.00151426	0.00441111
Exchange rate distortions	0.26	-7.60E-06	2.16E-05
Research and development	0.25	4.89E-05	0.000192033
Fraction speaking foreign language	0.22	0.000225097	0.00190593
Absolute latitude	0.21	-3.26E-06	6.27E-05
Population growth	0.20	0.0156664	0.102109
Area (scale effect)	0.20	-1.44E-08	3.13E-07
Ratio workers to population	0.20	-0.000509962	0.00372636
SD of black market premium	0.19	-7.72E-07	5.56E-06
Fraction Jewish	0.19	-0.000465403	0.00523741
Revolutions and coups	0.19	4.72E-05	0.00220733

Figure 3: R&D Indicator based on Nobel Prizes and the R&D Expenditures to GDP



Note: PIP stands for posterior inclusion probability and Mean denotes posterior mean of the R&D indicator effect on economic growth. For convenience, the posterior mean multiplied by 10^6.

structures gives ten different estimates of PIP and posterior mean. The results are given in Figure 3. The results show that irrespective of prior structures the R&D indicator exerts a positive effect on long-term economic growth and PIPs vary from 0.03 to 0.35. Clearly, as has been pointed out above, some prior structures are preferable to the others, so these results should not be overemphasized even though suggest the positive effect of R&D in all cases.

Further sensitivity analysis has been carried out by 1) we excluding the US and UK, which can be classified as outliers according to Figure 1, 2) including only 50 countries with with highest economic growth, 3) adjusting the formula in (10) for the calculation of the R&D indicator, as explained in the data section and 4) redefing RD_j as a dummy variable with four categories, with the following values: 0, for the countries without any Nobel prize (e.g. $RD_j = 0$), 1 for the countries with $RD_j < 1$, 2 for the countries with $RD_j > 1$, but except the US and UK, and 4 for the US and UK. The results indicate that the effect of R&D indicator is positive with the posterior inclusion probability between 0.1 and 0.25 depending on parameter and model prior structures, e.g. largely in line with the analysis above. These results are available upon request.

5 Concluding Remarks

We apply Bayesian model averaging technique to examine the role of research and development for long-term economic growth. We use the dataset of Fernandez et al. (2001a) that has been commonly employed to investigate the determinants of long-term growth using Bayesian techniques, but additionally include the indicator assessing the research and development intensity.

Even though, the previous studies examined the effect of dozens of regressors on long-term economic growth, R&D remianed untouched due to data unavailability. This is because the data on R&D with satisfactory time and country coverage became available mostly in 1990s, which is rather insufficient for cross-country growth regressions. We propose to overcome this issue by constructing the R&D indicator based on the number of Nobel prizes in science. We show that our indicator is correlated with recent data on R&D expenditures.

In terms of results, it is noteworthy that we use several parameter prior and model prior structures to shed light on the robustness of results. Subject to extensive sensitivity analysis, our results show that R&D exerts a positive effect of long-term growth.

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6 Appendix

Fernandez et al. (2001) dataset

The list of countries: Algeria, Argentina, Australia, Austria, Belgium, Bolivia, Botswana, Brazil, Cameroon, Canada, Chile, Colombia, Congo, Costa Rica, Cyprus, Denmark, Dominican Rep., Ecuador, El Salvador, Ethiopia, Finland, France, Germany West, Ghana, Greece, Guatemala, Haiti, Honduras, Hong Kong, India, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Korea, Madagascar, Malawi, Malaysia, Mexico, Morocco, Netherlands, Nicaragua, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Senegal, Singapore, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Tunisia, Turkey, Uganda, United Kingdom, United States, Uruguay, Venezuela, Zaire, Zambia, Zimbabwe.

The list of regressors: GDP level in 1960, Fraction Confucian, Life Expectancy, Equipment investment, Sub-Saharan dummy, Fraction GDP in mining, Fraction Hindu, Non-equipment investment, Rule of law, Degree of capitalism, Size labor force, Fraction Muslim, Fraction Protestants, Black market premium, Latin American dummy, Higher school enrollment, Ethnolinguistic fractionalization, Primary school enrollment, Civil liberties, Fraction Buddhist, Spanish colony dummy, Number of years open economy, Fraction of pop. speaking English, French colony dummy, Outward orientation, Political rights, Age, War dummy, British colony dummy, Fraction Catholic, Public education share, Primary exports, Exchange rate distortions, Research and development, Fraction speaking foreign language, Absolute latitude, Population growth, Area, (scale effect), Ratio workers to population, SD of black market premium, Fraction Jewish, Revolutions and coups

The details about the dataset are available in Fernandez et al. (2001).

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